

Ex. 1. Recap on Markov chains

$$X_1 \xrightarrow{\pi} X_2 \rightarrow X_3 \rightarrow \dots \rightarrow X_n, \quad X_i \in \Lambda = \{1, 2, \dots, 9\}$$

Transition probabilities

$$\begin{aligned} \pi(j|i) &= P(X_n = j | X_{n-1} = i) \quad \text{assumed } \checkmark \text{ homogeneous} \\ &= P(i \rightarrow j) \\ &= P(j|i) \end{aligned}$$

Transition matrix: Π : $\Pi_{ji} = \pi(j|i)$
↑ column
row

Stochastic matrix :

$$\sum_{j \in \Lambda} \pi(j|i) = 1 \quad \forall i \quad \Rightarrow \quad \vec{1} \Pi = \vec{1}$$

where $\vec{1} = (1, 1, \dots, 1)$

Propagation (Master equation):

$$\vec{P}_n = \Pi \vec{P}_{n-1}$$

i.e.

$$P_n(j) = \sum_i \pi(j|i) P_{n-1}(i)$$

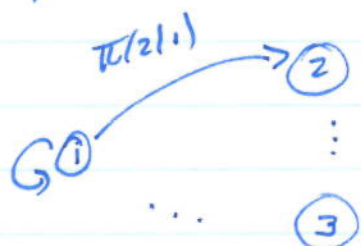
Stationary distribution:

$$\vec{P}^+ = \lim_{n \rightarrow \infty} \vec{P}_n = \lim_{n \rightarrow \infty} \Pi^{n-1} \vec{P}_1 \quad \text{ergodic Markov chain}$$

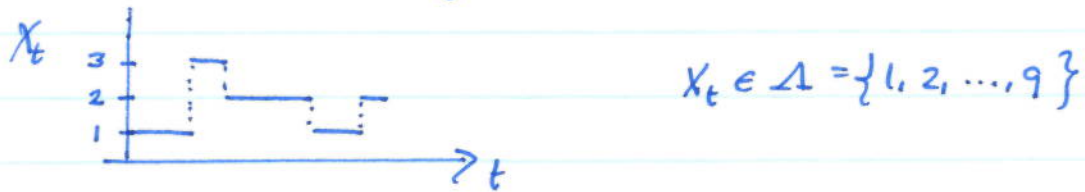
$$\vec{P}^+ = \Pi \vec{P}^+ \quad \text{fixed point of } \Pi$$

eigenvector with eigenvalue 1.

Graphical representation:



6.2. Continuous-time (jump) processes



- Transition probability:

$$\Pi_{ji}(s, t) = P(X_t = j \mid X_s = i) \quad t \geq s$$

- Homogeneous (stationary) case:

$$\begin{aligned} \Pi_{ji}(t) &= P(X_{t+s} = j \mid X_s = i) && \leftarrow \text{ind. of } s \\ &= P(X_t = j \mid X_0 = i) && \leftarrow \text{propagator} \\ &= P(i \rightarrow j \text{ in time } t) \end{aligned}$$

- Transition matrix: $\Pi(t) : \Pi_{ji}(t)$

\uparrow column
 \uparrow row

- $t=0 : \Pi(0) = \mathbb{1}$ no transitions, no evolution

- Stochastic matrix: $\sum_{j \in \Delta} \Pi_{ji}(t) = 1 \quad \forall i, t \geq 0$

$$\Rightarrow \vec{1} \Pi(t) = \vec{1}$$

- Propagation (Master equation):

$$P_j(t) = P(X_t = j) = \sum_i \Pi_{ji}(t) P_i(0)$$

$$\vec{P}(t) = \Pi(t) \vec{P}(0)$$

- Infinitesimal propagator:

$$\begin{aligned} \Pi(\Delta t) &= \Pi(0) + G \Delta t + O(\Delta t^2) \\ &= \mathbb{1} + G \Delta t + O(\Delta t^2) \end{aligned}$$

\leftarrow Generator

$$G = \lim_{\Delta t \rightarrow 0} \frac{\Pi(\Delta t) - \Pi(0)}{\Delta t} = \lim_{\Delta t \rightarrow 0} \frac{\Pi(\Delta t) - \mathbb{1}}{\Delta t}$$

$$\Pi(\Delta t) \approx \mathbb{1} + G \Delta t$$

- Off-diagonal part:

$$\Pi_{ji}(\Delta t) = G_{ji} \Delta t = W(i \rightarrow j) \Delta t \quad i \neq j$$

↳ transition rate
prob / unit time

- Diagonal part:

$$\Pi_{ii}(\Delta t) = 1 + G_{ii} \Delta t$$

- Normalization:

$$\begin{aligned} \sum_j \Pi_{ji}(\Delta t) &= \Pi_{ii}(\Delta t) + \sum_{j \neq i} \Pi_{ji}(\Delta t) \\ &= 1 + G_{ii} \Delta t + \sum_{j \neq i} G_{ji} \Delta t = 1 \end{aligned}$$

$$\Rightarrow G_{ii} + \sum_{j \neq i} G_{ji} = 0 \quad \text{or} \quad \sum_j G_{ji} = 0 \quad \text{columns sum to zero}$$

- G_{ii} is unspecified, so take

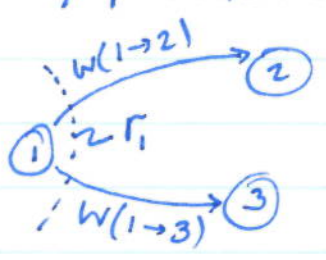
$$-G_{ii} = \sum_{j \neq i} G_{ji} = r_i \quad \text{escape rate from } i$$

- Complete form:

$$G_{ji} = W_{ji} - r_i \delta_{ij}$$

↳ off diagonal transition rate
↳ escape rate in diagonal

- Graphical representation:



- Propagation (Master equation):

$$\frac{d}{dt} \vec{P}(t) = G \vec{P}(t)$$

↳ generator

i.e.

$$\frac{d}{dt} P_j(t) = \sum_{i \neq j} \left(\underbrace{G_{ji} P_i(t)}_{\text{flow coming from } i} - \underbrace{G_{ij} P_j(t)}_{\text{flow leaving from } j} \right)$$

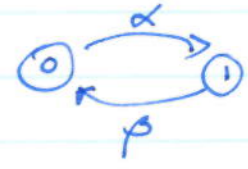
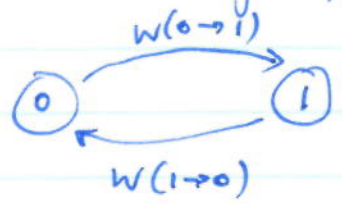
- Stationary distribution:

$$\frac{d}{dt} \vec{p}^* = 0 = G \vec{p}^*$$

$$\Rightarrow G \vec{p}^* = 0$$

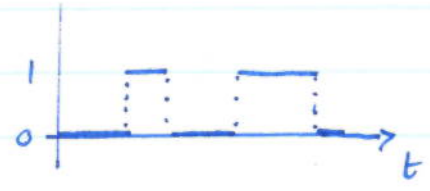
eigenvector of eigenvalue 0

Example: 2 state jump process $\Lambda = \{0, 1\}$



no self transi
no need to
specify
self transition

$$G = \begin{pmatrix} & w(1 \rightarrow 0) \\ w(0 \rightarrow 1) & \end{pmatrix} = \begin{pmatrix} -\alpha & \beta \\ \alpha & -\beta \end{pmatrix}$$



- Time spent in one state is exponentially-distributed:

$$P(X_t = i \text{ for } t \in [0, \tau]) = P(X_t = i \text{ for } t \in [0, \Delta t]) \cdot \dots \cdot P(X_t = i \text{ for } t \in [\tau - \Delta t, \tau])$$

$$= P(\text{no transition in } \Delta t)^{\tau/\Delta t}$$

$$= (\prod_{i,i}(\Delta t))^{\tau/\Delta t}$$

$$= (1 - r_i \Delta t)^{\tau/\Delta t}$$

$$n = \frac{\tau}{\Delta t}$$

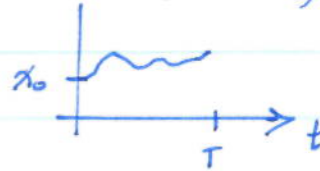
$$= (1 - r_i \frac{\tau}{n})^n$$

$$\rightarrow e^{-r_i \tau}$$

6.3 Ordinary differential equations (ODEs)

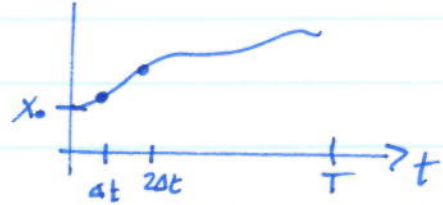
$$\begin{cases} \dot{x}(t) = f(x(t), t) \\ x(0) = x_0 \end{cases}$$

initial
"state" condition



Euler discretization:

$$\begin{cases} x(t + \Delta t) = x(t) + f(x(t), t) \Delta t \\ x(0) = x_0 \end{cases}$$



or

$$\begin{cases} \Delta x(t) = f(x(t), t) \Delta t \\ x(0) = x_0 \end{cases}$$

- Matlab code:

```
T = 5.0;
```

```
dt = 0.01;
```

```
n = floor(T/dt);
```

```
x = zeros(1, n+1);
```

```
x(1) = 4.0;
```

```
for i = 1:n
```

```
    x(i+1) = x(i) + f(x(i)) * dt;
```

```
end
```

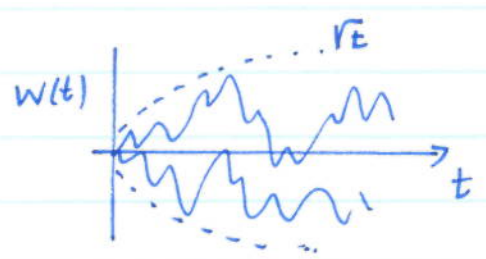
```
tspan = [0:dt:T];
```

```
plot(tspan, x);
```

6.4. Brownian motion or Wiener motion

$W(t), t \geq 0$ such that

- $W(0) = 0$
- $W(t) \sim \mathcal{N}(0, t) \Rightarrow E[W(t)] = 0 \quad \forall t$
 $\text{var } W(t) = t$



- Wiener increment:

- $W(t) - W(s) \sim \mathcal{N}(0, t-s) \quad t > s$
- Independent increments

- $W(t) = \lim_{n \rightarrow \infty} \sum_{i=1}^n \Delta W_n$
 $\Delta W_n \sim \mathcal{N}(0, \Delta t)$

$n = t/\Delta t$

- $\Delta W(t) \sim \mathcal{N}(0, \Delta t) = \sqrt{\Delta t} \mathcal{N}(0, 1)$

6.5. Stochastic differential equations (SDEs)

ODE

$$\begin{cases} \dot{x}(t) = f(x(t)) \\ x(0) = x_0 \end{cases}$$

initial condition

SDE \mathcal{N}^{rv}

$$\begin{cases} \dot{X}(t) = f(X(t)) + \dot{f}(t) \\ X(0) = x_0 \end{cases}$$

noise

- Noise model: $\dot{f}(t) = \frac{dW(t)}{dt}$ Gaussian white noise

- Discretization:

$$\begin{cases} x(t + \Delta t) = x(t) + f(x(t)) \Delta t \\ x(0) = x_0 \end{cases}$$

$$X(t + \Delta t) = X(t) + f(X(t)) \Delta t + \Delta W(t)$$

Wiener increment
 $\sim \mathcal{N}(0, \Delta t)$

$$dx(t) = f(x(t)) dt$$

$$dX(t) = f(X(t)) dt + \underbrace{dW(t)}_{\sim \mathcal{N}(0, dt)}$$

Euler

Euler-Maruyama

Examples:

1- Brownian motion: $dX(t) = dW(t)$ $f=0$
 $\Rightarrow X(t) = W(t)$

2- Drifted Brownian motion: $dX(t) = \overset{\text{drift}}{\mu dt} + \overset{\text{volatility}}{\sigma dW}$

3- Langevin equation or Ornstein-Uhlenbeck process:

$$dX(t) = -a X(t) dt + \sigma dW(t)$$

\hookrightarrow linear force

4- Geometric Brownian motion:

$$dS(t) = \mu S(t) dt + \sigma S(t) dW(t)$$

Simulation:

$$T = 5.0;$$

$$dt = 0.01;$$

$$n = \text{floor}(T/dt);$$

$$x = \text{zeros}(1, n+1);$$

$$x(1) = 4.0;$$

$$\text{sigma} = 1.0;$$

for $i = 1:n$

$$x(i+1) = x(i) + f(x(i)) * dt + \text{sigma} * \text{sqrt}(dt) * \text{randn};$$

end

$$t_{\text{span}} = [0:dt:T];$$

$$\text{plot}(t_{\text{span}}, x);$$

- Infinitesimal generator:

$$dX(t) = f(X(t))dt + \sigma dW(t)$$

$$X(t+dt) = X(t) + f(X(t))dt + \underbrace{\sigma dW(t)}_{\sim N(0, dt)}$$

$$x' = x + f(x) + \underbrace{\sigma z}_{\sim N(0, dt)}$$

Transformation of Gaussian RV:

$$\mathbb{P}_{\Delta t}(x'|x) = P(X_{t+\Delta t} = x' | X_t = x) \quad \text{Gaussian}$$

$$\downarrow$$

$$G(x'|x) \quad \text{generator}$$

- Fokker-Planck equation:

$$\frac{\partial}{\partial t} p(x,t) = -\frac{\partial}{\partial x} (f(x) p(x,t)) + \frac{\sigma^2}{2} \frac{\partial^2}{\partial x^2} p(x,t)$$

$$= L p(x,t) \quad \text{linear operator} = \text{FP operator}$$

- $L = \text{dual of } G$

$$= -\frac{\partial}{\partial x} f + \frac{\sigma^2}{2} \frac{\partial^2}{\partial x^2}$$

$$\Rightarrow G = L^\dagger = f \frac{\partial}{\partial x} + \frac{\sigma^2}{2} \frac{\partial^2}{\partial x^2} \quad \left(\left(\frac{\partial}{\partial x} \right)^\dagger = -\frac{\partial}{\partial x} \right)$$

- Stationary distribution:

$$\frac{\partial}{\partial t} p(x)^* = 0$$

$$\Rightarrow L p^* = 0$$